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8 Emotion dynamics as predictors of drinking behavior: idiographic and pooled approaches
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Abstract

The specific factors driving alcohol-related behavior and cognition likely vary from person to person. Many theories suggest emotions are pertinent to alcohol use. Emotions and how they change over time may provide an opportunity for more precise prediction of alcohol consumption. The present study applied statistical classification methods to idiographic time series data of emotions and emotion dynamics in order to identify person-specific and between-subjects predictors of future drinking-relevant behavior, affect, and cognition ($N = 33$). Participants were sent eight mobile phone surveys per day for 15 days. Each survey assessed the number of drinks consumed since the previous survey, as well as emotions, alcohol craving, and the desire to drink. Each participant's EMA data were prepared for analysis separately. To estimate emotion dynamics, we utilized the Generalized Local Linear Approximation. The data collected from each individual were split into training and testing sets for out-of-sample, person-specific validation. Elastic net regularization was used to select a subset of emotion and emotion dynamic variables to be used in models that predicted either alcohol consumption, craving, or wanting to drink roughly two hours in the future. To compare predictive performance, we tested both person-specific and between-subject prediction models. Averaging across participants, out-of-sample predictions of future drinking using idiographic models were 69% accurate. For craving, the mean out-of-sample R^2 value was .13. For wanting to drink, the mean out-of-sample R^2 value was .16. Idiographic prediction models exceeded nomothetic models in prediction accuracy. Using person-specific emotion and emotion dynamics can help predict future drinking behaviors.

49 **Introduction**

50 Given that alcohol consumption is a behavior enacted within the course of individual
51 lives, contexts, and demands, the specific factors driving alcohol consumption are likely
52 idiosyncratic. No universally accepted theory exists to explain the observed variability in alcohol
53 use both within- and between people, and despite research efforts and attention to alcohol use,
54 how these factors apply to or influence each person remains unknown [1,2]. Precise methods are
55 likely needed to investigate the cognitive, affective, behavioral, psychological, and social
56 mechanisms driving an individual to drink. One process of interest is emotion, and how patterns
57 of emotional experience may relate to alcohol consumption [3,4].

58 Emotions are defined broadly as intertwined shifts within the domains of subjective
59 experience, behavior, cognition, and peripheral physiology, unfolding over time within a person
60 [5,6]. They are the result of both internal and external changes in human experience and are
61 thought to communicate information about changing demands in the external environment. If we
62 are to evaluate how adaptive and functional an individual's emotional response is and the effect
63 of emotions on behavior, we must look at the dynamics of emotions within different contexts
64 over time [7]. Emotion dynamics are the individual trajectories, patterns, and regularities with
65 which emotions vary over time [8]. Several patterns have been operationalized in the literature
66 and are conceptualized as markers of emotional functioning [9].

67 Although emotions are relatively automatic reactions to differing environmental
68 demands, evidence indicates that they can be intentionally regulated. Emotion regulation refers
69 specifically to conscious attempts to alter aspects of intrinsic emotional experience (for full
70 discussion of emotion regulation, see [10,11]). Of relevance to the present study, alcohol and
71 other drug use is a course of action commonly associated with directly coercing emotional

response after an emotion has been expressed [5]. Some studies have correlated alcohol consumption with both positive and negative affective states and suggest that alcohol consumption tends to precede and follow strong emotion [12]. Recent research has also proposed a connection between emotion dysregulation and alcohol consumption, particularly in college students [13,14]. Thus, emotion dynamics may be a personalized warning signal of imminent state transitions in emotion and therefore behavior [15]. This would mean that emotion dynamics could be used to *predict* substance use before it occurs.

Alcohol Use and College Students

Alcohol use is considered by many as integral to the college student experience and is often thought of as a rite of passage during a temporary period in life where excessive consumption and potential negative consequences are both encouraged and expected [16,17]. Many college students who drink report more positive experiences than negative ones [18], and the extant literature suggests that it is normal for drinking to be more frequent during late adolescence and early adulthood [1,19]. Yet drinking is also considered one of the most pressing and prevalent issues of the college student population [19-21]. Many studies have examined differences in alcohol use between college students and noncollege peers, routinely finding higher rates of heavy drinking and alcohol related problems in college students in comparison to their same age noncollege peers [22].

Regarding the measurement of alcohol consumption, retrospective accounts of drinking behavior may underestimate the amount of actual alcohol consumed compared to momentary self-report surveys [23]. Ecological momentary assessment (EMA) resolves this issue by reducing the demands placed on autobiographical memory and minimizing retrospective bias, allowing researchers to obtain extensive behavioral data from participants at different times over

an extended survey period through answering short, momentary surveys typically delivered by smartphone [23]. Surveying participants in real time during their day-to-day lives likely increases ecological validity, capturing the contextual factors related to drinking as they occur in the presence of the behavior. Moreover, the intensive repeated measurements collected over many observations in EMA allows researchers to quantify the temporal relationships of emotion-related variables—extending analyses to dynamic features in the data [24,25]. Thus, EMA paradigms may be a key to comprehending what is motivating an individual to drink within their own lived experience [25,26].

Only a few studies to date have utilized EMA to explore emotion dynamics and drinking in college students. Gottfredson and Hussong [27] investigated how individual differences in emotion dysregulation (operationalized as the magnitude of within-day fluctuations in affect) were related to college students' tendency to drink within a 28-day EMA period. These authors found that individual differences in daily affect variation, and intra-individual fluctuations in affect variability, predicted daily alcohol use frequency and higher levels of self-reported drinking to cope [27]. On average, individuals who demonstrated a greater degree of change in affect were at higher risk for increased alcohol consumption than individuals who showed more stable affect. The valence of affect experienced alone was inconsequential nor did it predict alcohol use [27].

In line with these findings, Dvorak and colleagues [28] found that pre-drinking mood instability and positive mood were positively correlated with the likelihood of drinking on a given day in addition to the amount of alcohol consumed. Mood instability was again associated with increased daily alcohol use [28]. Simons and colleagues [29] found a significant within-person association between state negative affect and greater alcohol consumption when drinking,

however; at the between-person level, the inverse occurred, with greater negative affect predicting lesser alcohol use. These authors also found that affective lability (or variability) was associated with between-person differences in alcohol dependence symptoms [29]. Of note, Emery & Simons [30] did not find daytime difficulty in managing emotions to be significantly associated with nighttime drinking.

Consuming alcohol has mood altering effects [31,32]. Recent research findings utilizing EMA found that affect instability peaks in younger adults in comparison to older adults, and that younger adults are not as successful at regulating their emotions and their variability, which make them more prone to give in to desired behavior (such as alcohol use) despite that behavior interfering with their goals [33]. Given these patterns, it logically follows that people, specifically undergraduates, might drink in response to emotional instability or variability—either to modify their emotional state or to enhance it. But data supporting this idea is equivocal. If it is the case that an individual is using alcohol in response to their emotions, there should be reliable patterns of emotion dynamics that precede drinking behavior. The current study sought to investigate this assumption, in order to test if targeting emotional antecedents to drinking behavior could reliably predict future alcohol consumption. Doing so could inform effective preventive and protective interventions, as current interventions for college students need improvement [19,34].

Idiographic, Nomothetic and Pooled Approaches

The aim of nomothetic research is to derive an understanding of what is generally true of a population by examining interindividual variation (variation between people), whereas the aim of *idiographic* research is to derive an understanding of what is generally true of a specific individual by examining intraindividual variation (variation within a specific person over time)

[35,36,37]. In light of data that suggests there is marked individual variability in emotional experience and drinking behavior, group level patterns may not accurately depict the relationship between emotions and alcohol consumption for each person. However, it has been argued that within- and between-person approaches contribute distinct and essential information [25]. A *pooled* approach approximates a between-person approach, but retains intraindividual variation by mean-centering within-person information for each participant in order to generate a model for the entire group. To this end, we sought to investigate idiographic and pooled models to see which made better predictions of drinking behavior based on emotion variables.

The Present Study

The present study addressed the following questions using an EMA paradigm with a college student sample: 1) can drinking events be accurately predicted by temporal changes or patterns in emotion within-person, 2) can changes in emotion significantly contribute to explaining craving and wanting to drink in individual participants to better understand what precedes alcohol use within-person and 3) do these emotion patterns capture emotion dynamics specific to the individual in relation to drinking behavior, or are these processes relatively similar across our sample experiencing similar social and cultural contexts? Given that the present sample was relatively homogeneous (see Method), there is a possibility that common influences may provide greater predictive utility. Prior research with the current sample has demonstrated predictive utility in pooled prediction modeling [2].

To produce both *pooled* and fully idiographic prediction models, statistical classification methods were applied to idiographic time series data. These procedures defined a large set of potential predictors pertaining to time, emotions, and emotion dynamics, then utilized variable selection methods to exclude less-predictive variables per model, and then generated prediction

models per person. We accounted for the shape of the behavior's temporal variation, such as time-of-day or day-of-the-week [38], using temporal covariates.

To test how well group level information could be used to predict individual behavior, fully idiographic predictions were compared to a single pooled prediction model, composed of concatenated, person-mean-centered data from all participants, which were then tested on a person-by-person basis on individual holdout data. In other words, within the pooled approach a single set of predictive coefficients were generated from the concatenated data. Then, this single set of predictive coefficients was used to generate predictions from the idiographic holdout data on a person-by-person basis—reflecting the degree to which a set of shared patterns between individuals can predict momentary behavior within individuals. Thus, in the present study, all assessments of prediction accuracy were tested on person-specific holdout data, assessing the degree to which idiographic or pooled models accurately predict future outcomes at the person level.

We hypothesized that emotions and temporal patterns pertaining to changes in emotion would accurately predict subsequent alcohol consumption, and these specific emotion states or temporal changes in emotion that lead to alcohol consumption would vary by person. This would be evidenced by the idiographic models demonstrating a higher Area Under the Curve (AUC), sensitivity, and specificity average compared to the pooled model averages from person to person. In addition, we predicted that the idiographic models would have a lower Brier score average in comparison to the pooled nomothetic models. We predicted that averages for craving and wanting to drink would return a larger proportion of explained variance (as indexed by R^2) for the idiographic models in comparison to the pooled model results.

Method

Participants

Participants were recruited through an undergraduate research participation pool at the University of California, Berkeley. Potential participants were directed to an online survey to screen for study eligibility. Inclusion criteria required that participants be at least 18 years of age, have English-language proficiency, be able to regularly access a web-enabled mobile phone, have a history of alcohol consumption (at least one sip) in their lifetime, and have had thoughts of consuming alcohol at least once in the previous month. Potential participants were not required to have either desire or motivation to change their drinking behavior.

Thirty-three participants completed the present study. Participants were adults ($M_{age} = 19$; $SD = 2.75$, range: 18-30) living in the San Francisco Bay Area who indicated they had used alcohol at some point in their lifetime via self-report. Twenty-seven participants (90%) identified as female and 2 identified as male, with one person who preferred to not disclose. Participants were 37% white, 33% Asian/Pacific Islander, 7% Hispanic or Latino, 20% mixed or 'other', and 3% who preferred not to disclose. Participants indicated their sexual orientation as 80% heterosexual, 3% homosexual, 13% bisexual/queer, and 3% who preferred not to disclose. When entering the study, participants reported consuming alcohol on an average of 1.67 days in the past week ($SD = 1.37$, range = 0-4) and an average of 4.23 ($SD = 2.42$, range: 1-12) drinks consumed on drinking days.

Procedure

All study procedures were approved by the University of California, Berkeley Committee for the Protection of Human Subjects. The present study was a reanalysis of Soyster et al. [2].

Participants eligible for the parent study were invited to the Idiographic Dynamics Lab at UC Berkeley for study enrollment and completion of baseline assessments. After completing the baseline assessment, participants were introduced to the EMA survey system and were then instructed how to estimate standard drink equivalents. Participants completed EMA surveys eight-times-daily for a 15-day period. Surveys were sent on a block-randomized schedule, initiating a survey prompt within subsequent two-hour windows throughout the day. Notifications were sent to participants' mobile phones as hyperlinked text messages. Initial survey notifications for each day were scheduled based on participant-reported wake-up time. EMA surveys asked participants to rate their current experience of each variable on a 0 (not at all) to 100 (as much as possible) visual analog slider. The survey item assessing the number of drinks since the previous survey was answered as a count. Participants who completed at least 80% of the mobile phone surveys were reimbursed with partial course credit.

Baseline measures

Demographics

Demographic measures included participants' age, biological sex, gender identity, sexual orientation, racial/ethnic identity, alcohol use history, and surveys assessing psychological functioning.

EMA survey measures

Survey procedure

Each survey assessed the number of standard drinks consumed since the previous survey, as well as positive affect, negative affect, alcohol craving, drinking expectancies, perceived alcohol

consumption norms, impulsivity, and social and situational context. Table 1 contains the complete list of survey items and their wordings.

Table 1. Items asked in EMA Surveys.

Items Assessed Through EMA	Variables Derived From Time
Since your last survey; how many alcoholic drinks have you had?	Linear time
I feel comfortable in my current location	Quadratic time
I feel stressed	Cubic time
I feel down/depressed	24-hour cosine
I feel calm/relaxed	24-hour sine
I currently feel pressure to drink	12-hour cosine
I feel enthusiastic	12-hour sine
I feel happy	Weekly cosine
I am having conflict/fighting with others	Weekly sine
I am craving alcohol	Monday
I am feeling impulsive	Tuesday
A drink would make me feel better right now	Wednesday
What percentage of Berkeley students do you think are drinking alcohol right now?	Thursday
I would like to drink	Friday
I feel able to delay gratification	Saturday
I feel angry	Sunday
How many alcoholic drinks do you think you'll consume today?	Survey 1 of the day
Last night; my sleep was restless or unsatisfying	Survey 2 of the day
Last night; I had difficulty falling or staying asleep	Survey 3 of the day
How many hours did you sleep last night?	Survey 4 of the day
	Survey 5 of the day
	Survey 6 of the day
	Survey 7 of the day
	Survey 8 of the day

Variables derived by time were not directly asked, but were included in prediction models.

Survey Completion

The mean number of completed surveys across all participants ($N = 33$) was 107.6 ($SD = 25.6$), with a minimum of 11 and a maximum of 129. The mean, maximum, minimum, and standard deviation was determined for retained participants before the multiple imputation step of data cleaning was completed ($M = 118$, range = 129 - 104, $SD = 6.72$).

Data preparation and analysis

Each participant's EMA data were prepared for analysis separately. Missing data were handled by multiple imputation via the Fourier lagged k -nearest neighbors (FL k -NN) method for time-series data that incorporates time lagged correlations both within and across variables by combining k -NN imputation and the Fourier transform [39]. We set an imputation threshold per participant of 25% missingness; otherwise, imputation was not performed, and participant data were excluded from analysis ($N = 7$). Imputation was performed in MatLab (R2020b) using imputation code provided by Rahman [39], and provided complete datasets per participant for analysis.

Next, we used survey time stamps to calculate cumulative time since the first EMA survey, then checked and cleaned the data frame to have a uniform structure that reflected the survey procedure of eight surveys a day. Then, we created variables for survey number, day of the week, and cycles of 12-hr, 24-hr, and weekly frequency.

Consistent with the methods provided by Flury and Levri [40], the latter variables were constructed from sine and cosine terms. We then transformed drinking data so that each observation represented whether any drinking had occurred since the last observation. For the models of alcohol consumption, we assessed participants' data for the frequency and distribution of drinking events. We excluded participants from the drank/did not drink analysis for insufficient frequency of survey responses or for reporting so few drinking occasions during the

survey period that k-fold cross-validation (see below) could not be run ($N=3$). However, these participants were included in the analyses of continuous craving and wanting to drink variables.

For the craving and wanting to drink models ($N=26$), participants' data were assessed for variability in reported craving and wanting to drink. We omitted participants from the craving and wanting to drink analysis if they did not meet an imputation threshold of 25% missingness, because imputation could not be performed, and the participant data were excluded from analysis for lack of variability ($N=7$).

We set all temporal variables and the binary drinking variable forward in time by one observation. The data frame then provided row-wise relationships wherein all temporal variables were aligned in time with the occurrence of drinking events, and all remaining predictor variables were lagged predictors. This data structure allowed for k-fold cross-validation of a time series without violating the contiguity, or proximity, of the data. All prediction models in the present analysis were lagged models-predicting drinking events, craving, and wanting to drink roughly two hours in the future. Table 2 presents the complete feature space for all prediction models.

Table 2. Possibility space in all prediction models.

Items Assessed Through EMA	Variables Derived From Time
Since your last survey; how many alcoholic drinks have you had?	Linear time
I feel stressed	Quadratic time
I feel stressed 1st order derivative	Cubic time
I feel stressed 2nd order derivative	24-hour cosine
I feel down/depressed	24-hour sine
I feel down/depressed 1st order derivative	12-hour sine
I feel down/depressed 2nd order derivative	12-hour cosine
I feel calm/relaxed	Weekly cosine
I feel calm/relaxed 1st order derivative	Weekly sine

I feel calm/relaxed 2nd order derivative	Monday
I feel enthusiastic	Tuesday
I feel enthusiastic 1st order derivative	Wednesday
I feel enthusiastic 2nd order derivative	Thursday
I feel happy	Friday
I feel happy 1st order derivative	Saturday
I feel happy 2nd order derivative	Sunday
I am craving alcohol	Survey 1 of the day
I would like to drink	Survey 2 of the day
I feel angry	Survey 3 of the day
I feel angry 1st order derivative	Survey 4 of the day
I feel angry 2nd order derivative	Survey 5 of the day
	Survey 6 of the day
	Survey 7 of the day
	Survey 8 of the day

Variables derived by time and derivatives of emotion variables were not directly asked of participants, but were possibly included in prediction models.

We chose the survey items *I feel happy*, *I feel enthusiastic*, *I feel calm/relaxed*, *I feel down/depressed*, *I feel stressed*, and *I feel angry* as representing distinct emotions participants rated for the duration of the EMA surveys. In order to estimate emotion dynamics in the present data, we conceptualized participants as dynamic systems within a continuous time framework—wherein people are systems whose current emotional state depends on their preceding states—in order to describe how emotion variables change at regular intervals over time [41-44]. That is, assuming that emotions are constantly changing over time, we can assume the slope of change is also constantly changing [43]. One way to model these emotions is to calculate their derivatives, or changes with respect to time [43,45]. To do this, we utilized the Generalized Local Linear Approximation (GLLA) function [42] in R (R Core Team, 2021). We chose GLLA specifically for its ability to use any number of observations to estimate a derivative within time series data,

its tendency to produce a narrowed sampling distribution than Local Linear Approximation, and its production of observed instead of latent estimates [42].

For each emotion item, we employed the GLLA function after these variables were mean-centered in order to obtain the following variables for each emotion at every time point: the *level*, or the person's score of that emotion at some point in time within the raw data (the 0th order derivative); *velocity*, or the speed in one direction that a person's score of emotion is changing over time (the 1st order derivative); and the *acceleration*, or the rate at which velocity is changing over time (the 2nd order derivative) [42]. This procedure provided three derivatives of each emotion item that we then used as independent variables within the models.

Constructing prediction models

In order to predict future drinking from a personalized subset of the study variables pertaining to emotion, time, and emotion dynamics, a data driven approach was required to select the most relevant of those variables per person. The current study was exploratory and data driven. Because we had no *a priori* assumptions about which emotions and associated dynamics would best predict each person's drinking behavior, machine learning methods were employed to evaluate the predictive value of each variable for each person.

Penalized regression is a supervised machine learning technique, which considers two main problems: parameter estimation and variable selection [46]. Choosing the most relevant variables from the set of all possible variables to use as predictors in a model is essential for accurate prediction. Shrinkage methods, also called regularization, significantly reduces variance in the produced model, in addition to performing variable selection to minimize prediction error [47]. The least absolute shrinkage and selection operator (LASSO) is a method that shrinks estimated regression coefficients via L_1 regularization, iteratively excluding variables with a

regression coefficient of zero from the model [46,47]. Ridge regression, minimizes the squared sum of the coefficients (L_2 regularization). Thus, contrary to the LASSO, ridge penalization never shrinks coefficients to zero. Both approaches intend to achieve better prediction through a bias-variance tradeoff [48]. Both methods tend to perform well and prevent overfitting of data [46]. However, both methods have their limitations. Ridge regression often fails to produce the most precise model because it retains the full set of predictors, regardless of their contribution to the model. The LASSO often lacks the ability to distinguish the most relevant predictors of the model, a desired effect known as grouping [48].

Elastic net regularization is a blend of LASSO and ridge that intends to resolve these limitations while still making use of their advantages [48]. The current study used elastic net regularization to select the independent emotion variables for idiographic prediction models. Zou and colleagues [48] explain that the elastic net encourages strongly correlated predictors to be either in or out of the model together (the grouping effect LASSO lacks), and is superior in prediction accuracy in comparison to either the LASSO or ridge regression alone.

The present study used the *glmnet* package [49] in R for conducting all elastic net regressions. Specifically, we used the *cv.glmnet* function in *glmnet* to run a k-fold cross-validation with 10 folds. Cross-validation was employed to select levels of lambda, the hyperparameter that controls the level of penalization in the model. The *glmnet* function runs a set of models at iteratively greater levels of lambda. The degree of penalization that minimizes the prediction error is chosen as the best-fit model. An additional hyperparameter, alpha, determines the degree to which the model utilizes LASSO versus ridge regression. Alpha has a maximum of 1.00 and a minimum of 0.00, with the former indicating pure LASSO regression and the latter indicating pure ridge regression. In the present study, all models were initially run

at an alpha of .50. If no variables were retained, alpha was decreased by increments of .05 until at least one nonzero coefficient was retained.

Each participant's time series was randomly split-halved to create training and testing data sets. Training sets were independently used to create fully idiographic prediction models and concatenated to create a single pooled model (see below). For both pooled and fully idiographic approaches, the same testing (holdout) set was used to evaluate prediction accuracy.

For fully idiographic models, elastic net regression models were fit to each participants' training data and then tested on the testing data to evaluate out of sample performance. For pooled predictions, all 33 training models were person-mean-centered and concatenated into a single data structure. Whereas, a unique (person-specific) prediction model was used to evaluate fully idiographic predictions, a single, pooled prediction model was used to make all pooled predictions (although, as noted above, these predictions were carried out on the idiographic testing sets). The area under the receiver operating characteristic curve (AUC) indicates how well the model is able to predict each drinking event of interest. The sensitivity of the model reports how accurately the model predicts how often someone drinks. The specificity reports how accurately the model predicts when someone did not drink.

The resulting coefficients from the training set after this procedure were then used to predict drinking events in the testing data set. The *pROC* function in the *pROC* package [50] in R was then employed to determine AUC, sensitivity, and specificity for predictions of each participant's future drinking events in the testing data set. Brier score was calculated separately. Brier score represents the mean squared difference between an observed binary outcome and the model estimated probability of that outcome occurring, with lower scores indicating stronger

predictive performance [51]. To calculate effect size, we used established methods for converting AUC to Cohen's d [52].

For craving and wanting to drink models, we used elastic net regularization to generate predictions using variable selection of future continuous ratings of the dependent variables. The same subset of predictors used in the drank/did not drink models were not necessarily the same used to predict craving and wanting to drink. We calculated R^2 values to estimate model fit in the testing data set.

Pooled prediction models

To test the accuracy of a single pooled prediction that shared information from all participants, the training models from each participant's time series data were concatenated to generate a single aggregate data frame for drinking events analysis ($N = 23$) and craving and wanting to drink analyses ($N = 26$). Every variable was person-mean-centered to account for nesting within persons across multiple measurements. Lag-1 structure within each individual data set prior to concatenation was created to make sure no between-subject lags existed in the aggregated data. We then concatenated the 23 lagged, person-mean-centered times series into a long-format nomothetic data frame for drinking events, and 26 lagged, person-mean-centered times series into the same long-format nomothetic data frame for craving and wanting to drink. The elastic net procedures detailed above were then applied to each set of the pooled data. The aggregated models were produced with $\alpha = .50$. The fixed-effect coefficients from these models were then applied to the out-of-sample holdout data for each individual to predict drinking, craving, and wanting drink, person by person.

Results

Elastic net regularization

Dichotomous (drank/did not drink) predictions

The results of all 23 person-specific dichotomous prediction models are presented in Table 3 and Fig 1. The mean out-of-sample AUC was 0.69 (SD = 0.14, range = 0.53 to 0.90, median = 0.67, Cohen's $d = 0.70$), showing a medium to large effect size. The mean sensitivity was 0.74 (SD = 0.19; range = 0.33 to 1.00), and the mean specificity was 0.70 (SD = 0.18; range = 0.36 to 0.98). The mean Brier score was 0.117 (SD = .05; range = .047 to .221). These findings indicate that the person-specific models in the present study were 69% accurate on average, with an average of 74% accuracy for predicting presence and 70% accuracy for predicting absence of a drinking episode.

Fig 1. Histograms of Idiographic and Pooled Model Results.

Table 3. Person-specific dichotomous (drank/did not drink) prediction model results.

<u>ID</u>	<u>AUC</u>	<u>Sensitivity</u>	<u>Specificity</u>	<u>Brier</u>	<u># of Retained Variables</u>	<u>Retained Variables</u>	<u># of Retained Self Report Variables</u>
1	0.67	0.78	0.59	0.13	6	4,7,9,22,25,43	1
2	0.84	0.78	0.83	0.11	8	11,12,13,20,22,23,24,43	0
3	0.65	0.58	0.70	0.17	13	10,13,18,21,25,26,29,31,32,33,40,42,43	0
4	0.78	1.00	0.50	0.13	24	3,4,7,10,11,12,13,16,17,19,20,21,25,26,28,29,31,32,34,33,36,37,38,43	2
5	0.57	0.33	0.98	0.09	3	26,28,43	0
6	0.83	1.00	0.65	0.12	9	11,20,21,25,	0

						26,27,30,36,43	
7	0.53	0.57	0.65	0.12	19	2,4,6,31,39,41, 37,38,7,8,11,12 ,13,18,19,20,21 ,22,43	3
8	0.80	0.80	0.80	0.09	12	1,5,6,12,16,24, 28,29,32,36,42, 43	3
9	0.78	0.53	0.93	0.22	18	1,6,36,34,41,37 ,9,13,15,18,19, 22,23,25,26,27, 28,43	2
10	0.64	0.89	0.51	0.14	6	1,12,23,25,29, 43	1
12	0.90	0.71	0.95	0.12	20	2,4,5,6,8,12,19, 20,21,23,24,25, 28,30,34,35,44 1,42,38,43	4
14	0.68	0.91	0.43	0.16	7	21,25,26,31,41, 42,43	0
15	0.53	0.54	0.52	0.18	12	7,8,12,21,29, 30,31,35,37,39, 41,42	0
17	0.66	0.69	0.61	0.18	42	1,2,3,4,5,6,7,8, 9,10,11,12,13, 15,16,17,18,19, 20,21,22,23,24, 25,26,27,28,29, 30,31,32,33,34, 35,36,37,38,39, 40,41,42,43	6
18	0.85	0.80	0.80	0.06	9	1,3,9,13,21,32, 33,41,43	2
19	0.89	1.00	0.85	0.06	18	1,2,4,6,12,13, 21,23,27,28,29, 32,33, 34,36,38,41,43	4
21	0.67	0.60	0.76	0.19	24	4,6,7,8,10,11, 13,15,16,21,22, 24,25,27,28,29, 30,31,33,36,39, 40,43	2
22	0.50	0.75	0.47	0.08	16	1,2,3,10,12,13,	3

						15,21,23,25,26, 32,34,36,43	
23	0.56	0.67	0.67	0.07	10	3,6,10,21,25, 26,38,40,42,43	2
25	0.85	1.00	0.71	0.06	21	2,3,4,5,7,12,15, 16,21,22,24,25, 28,29,31,32, 33,34,36,41,43	4
29	0.72	0.57	0.85	0.11	14	1,2,3,4,10,13, 16,24,25,27,30, 38,41,43	4
30	0.50	1.00	0.36	0.07	10	5,6,13,17,19, 28,30,33,38,43	2
32	0.56	0.50	0.89	0.05	34	2,4,5,6,7,8,9, 10,11,13,15, 16,17,18,19, 20,21,22,24, 25,27,28,29,30, 31,32,35,36,37, 38,39,41,42,43	4
Avg	0.69	0.74	0.70	0.12	15		2

Variables derived by time and derivatives of emotion variables were not directly asked of participants. 1= Stressed 2= Down/depressed, 3= Calm, 4= Enthusiastic, 5= Happy, 6= Angry, 7= Monday, 8= Tuesday, 9= Wednesday, 10= Thursday, 11= Friday, 12= Saturday, 13= Sunday, 14= Survey 1, 15= Survey 2, 16= Survey 3, 17= Survey 4, 18= Survey 5, 19= Survey 6, 20= Survey 7, 21= Survey 8, 22= Linear time, 23= Quadratic time, 24= Cubic time, 25= 12-hour cosine, 26= 12-hour sine, 27= 24-hour cosine, 28= 24-hour sine, 29= weekly cosine, 30= weekly sine, 31 = Happy 1st order derivative, 32 = Happy 2nd order derivative, 33 = Calm 1st order derivative, 34 = Calm 2nd order derivative, 35 = Enthusiastic 1st order derivative, 36 = Enthusiastic 2nd order derivative, 37 = Angry 1st order derivative, 38 = Angry 2nd order derivative, 39 = Down 1st order derivative, 40 = Down 2nd order derivative, 41 = Stressed 1st order derivative, 42 = Stressed 2nd order derivative, 43 = Did participant drink anything since the last survey (yes/no).

Continuous predictions for ‘craving’ and ‘wanting to drink’

The results for all 26 person-specific models for ‘craving’ and ‘wanting to drink’ are presented in Table 4, and Fig 1. For ‘craving’, the mean out-of-sample R^2 value was 0.13 (SD = 0.11; range = 0.00 to 0.49; Cohen’s $d = 0.77$), showing a medium to large effect size. For ‘wanting to drink’,

the mean out-of-sample R^2 value was 0.16 (SD = 0.14; range = 0.00 to 0.44; Cohen's $d = 0.87$), showing a large effect size.

Table 4. Person-specific R^2 Values for 'Craving' and 'Want to Drink' Models.

ID	R^2 Craving	# of Retained Variables	Retained Variables	# of Retained Self Report Variables	R^2 Want to Drink	# of Retained Variables	Retained Variables	# of Retained Self Report Variables
1	0.04	1	25	0	0.06	1	25	0
2	0.18	8	2,37,10,12, 20,22,26,30	1	0.44	11	2,11,12,20, 22,25,26, 29,30,31,4 3	1
3	0.10	6	13,16,26, 29,30,32	0	0.16	5	11,13,19, 30,32	0
4	0.04	18	1,7,10,13,16 ,18,19,20, 22,23,28,29, 31,36,38,39, 41,43	1	0.01	9	7,9,10,13, 20,23,26, 39,43	0
5	0.21	14	1,4,5,6,11, 19,23,25,26, 27,28,29,38, 43	4	0.32	16	2,5,9,10,11 ,15,20,22, 23,25,26, 27,29,32, 34, 43	2
6	0.15	3	22,26,27	0	0.20	4	2,3,16,26	2
7	0.07	16	3,33,35,36,3 7,7,8,10,13, 20,22,24,26, 28,29,30	1	0.04	15	3,6,7,10,12 ,20,22,24,2 6,28,29,30, 33,36,42	2
8	0.24	3	12,29,43	0	0.41	8	1,11,12,19, 26,29,39, 43	1
9	0.31	6	11,12,21,25, 26,41	0	0.34	10	36,33,8,11, 15,16,21, 25,26,30	0
10	0.01	2	21,43	0	0.09	4	11,25,29,4 3	0
12	0.24	8	3,12,20,25,	1	0.28	15	1,4,6,10,	3

			26,27,35,39				12,18,20, 25,26,27, 29,34,39, 40,43	
13	0.01	6	1,2,7,17,36, 40	2	0.00	4	2,12,19,30	1
14	0.26	8	10,23,26,31, 34,41,42,43	0	0.29	6	4,10,23,31, 40,43	1
15	0.16	42	1,2,3,4,5,6, 7,8,9,10,11, 12,13,15,16, 17,18,19,20, 21,22,23,24, 25,26,27,28, 29,30,31,32, 33,34,35,36, 37,38,29,40, 41,42,43	6	0.07	7	7,22,23,29, 32,38,39	0
16	0.10	9	1,12,20,22, 24,26,27,30, 43	1	0.03	11	9,12,17,18, 20,22,27, 30,38,41, 43	0
17	0.09	2	2,12	1	0.07	23	1,2,3,4,7,8, 11,12,13, 15,16,17, 18,19,22, 28,29,30, 33,34,36, 37,38	4
18	0.09	11	1,3,4,10,22, 23,24,30,39, 40,43	3	0.10	3	21,22,24	0
19	0.15	16	3,4,6,7,11, 13,17,18,19, 22,26,29,30, 31,37,39	3	0.01	1	37	0
21	0.49	15	1,4,5,6,10, 11,13,18,19, 20,23,26,29, 41,43	4	0.43	11	1,2,34,39, 41,9,10,13, 18,21,29	2
22	0.10	9	1,3,7,10,16, 21,24,26,30	2	0.19	17	4,5,9,10,11, 16,17,23, 24,26,28,	2

							30,36,34, 41,42,37	
23	0.12	1	22	0	0.21	4	6,37,22,24	1
25	0.00	1	2	1	0.17	12	11,16,21, 31,23,24, 27,28,30, 34,35,42	0
27	0.00	1	37	0	0.00	2	6,37	1
29	0.22	7	2,5,9,11,18, 24,28	2	0.19	12	1,2,3,4,32, 35,7,9,10, 11,24,29	4
30	0.02	12	2,8,11,13,21 ,23,24,25, 29,30,33,35	1	0.07	5	37,38,8,29, 30	0
32	0.05	4	17,25,28,34	0	0.00	6	20,25,30, 39,42,43	0
Avg	0.13	9		1	0.16	9		1

Variables derived by time and derivatives of emotion variables were not directly asked of participants. 1= Stressed 2= Down/depressed, 3= Calm, 4= Enthusiastic, 5= Happy, 6= Angry, 7= Monday, 8= Tuesday, 9=Wednesday, 10= Thursday, 11= Friday, 12= Saturday, 13= Sunday, 14= Survey 1, 15= Survey 2, 16= Survey 3, 17= Survey 4, 18= Survey 5, 19= Survey 6, 20= Survey 7, 21= Survey 8, 22= Linear time, 23= Quadratic time, 24= Cubic time, 25=12-hour cosine, 26= 12-hour sine, 27= 24-hour cosine, 28= 24-hour sine, 29= weekly cosine, 30= weekly sine, 31 = Happy 1st order derivative, 32 = Happy 2nd order derivative, 33 = Calm 1st order derivative, 34 = Calm 2nd order derivative, 35 = Enthusiastic 1st order derivative, 36 = Enthusiastic 2nd order derivative, 37 = Angry 1st order derivative, 38 = Angry 2nd order derivative, 39 = Down 1st order derivative, 40 = Down 2nd order derivative, 41 = Stressed 1st order derivative, 42 = Stressed 2nd order derivative, 43 = Did participant drink anything since the last survey (yes/no).

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424 Pooled prediction models

425 The results of all pooled prediction models are presented in Table 5 and Fig 1. In predicting
426 future outcomes in the out-of-sample idiographic time series, these results reflect the accuracy of
427 the fixed-effect coefficients of the pooled models. For the first version of the drank/did not drink
428 analysis (Table 5), the mean out-of-sample AUC for person-level predictions from the pooled
429 elastic net prediction coefficients was 0.59 (SD = 0.07; range = 0.55 to 0.74, median = 0.58,

Cohen's $d = 0.32$), showing a small effect size. The mean sensitivity was 0.75 (SD = 0.20; range = 0.30 to 1.00), and the mean specificity was 0.56 (SD = 0.21; range = 0.17 to 0.96). The mean Brier score was 0.284 (SD = .07; range = 0.150 to 0.407). These findings indicate that the person-level tests of the pooled elastic net predictors were 59% accurate on average, with an average of 75% accuracy for predicting presence and 56% accuracy for predicting absence of a drinking episode.

Table 5. Pooled elastic net model results.

ID	AUC	Sensitivity	Specificity	Brier	R ² Craving	R ² Want to Drink
1	0.55	1.00	0.17	0.27	0.01	0.03
2	0.67	0.89	0.50	0.22	0.19	0.18
3	0.62	0.50	0.86	0.36	0.03	0.16
4	0.58	0.73	0.48	0.34	0.01	0.07
5	0.68	1.00	0.24	0.41	0.03	0.02
6	0.51	0.30	0.91	0.24	0.06	0.10
7	0.51	0.71	0.49	0.40	0.04	0.00
8	0.66	1.00	0.53	0.22	0.24	0.24
9	0.64	0.80	0.45	0.34	0.17	0.16
10	0.74	0.89	0.57	0.18	0.11	0.18
12	0.69	0.94	0.49	0.27	0.09	0.07
14	0.58	0.55	0.68	0.24	0.14	0.12
15	0.59	0.46	0.81	0.28	0.01	0.04
17	0.50	0.85	0.29	0.33	0.02	0.01
18	0.50	0.80	0.43	0.30	0.17	0.07
19	0.58	0.33	0.96	0.21	0.00	0.00
21	0.54	0.90	0.42	0.25	0.18	0.34
22	0.63	0.75	0.67	0.40	0.00	0.00
23	0.57	1.00	0.40	0.15	0.00	0.00
25	0.51	0.75	0.47	0.24	0.02	0.00
29	0.54	0.57	0.54	0.33	0.10	0.03

30	0.66	1.00	0.62	0.25	0.03	0.05
32	0.57	0.50	0.89	0.31	0.04	0.00
Avg	0.59	0.75	0.56	0.284	0.07	0.08

Continuous predictions for ‘craving’ and ‘wanting to drink’

The results for all 26 pooled models for ‘craving’ and ‘wanting to drink’ are presented in Fig 1. For ‘craving’, the mean out-sample R^2 value was 0.07 (SD = 0.07; range = 0.00 to 0.23; Cohen’s $d = .55$), showing a medium effect size. For ‘wanting to drink’, the mean out-of-sample R^2 value was 0.08 (SD = 0.09, range = 0.00 to 0.22; Cohen’s $d = 0.59$), showing a medium effect size. The results of which variables were retained and how frequently they were retained for each model are featured in Table 6.

Table 6. Frequencies of variable retention by person-specific model type.

Variable	1	2	3	Variable	1	2	3	Variable	1	2	3
Enthusiastic	10	5	5	Calm 1st derivative	7	3	3	Survey 4	4	4	3
Happy	6	4	2	Calm 2nd derivative	7	3	6	Survey 5	5	5	4
Angry	10	4	4	Stress 1st derivative	11	5	3	Survey 6	7	5	4
Down	8	7	7	Stress 2nd derivative	8	2	4	Survey 7	7	7	7
Calm	7	6	4	Monday	8	6	5	Survey 8	15	5	4
Stressed	8	8	5	Tuesday	6	3	3	Linear Time	8	9	8
Enthusiastic 1st derivative	4	4	2	Wednesday	5	2	6	Quadratic time	7	7	6
Enthusiastic 2nd derivative	10	4	4	Thursday	8	8	8	Cubic Time	9	7	6
Happy 1st derivative	9	4	3	Friday	7	7	10	12-hour cosine	15	7	7

Happy 2nd derivative	9	2	4	Saturday	11	7	7	12-hour sine	9	13	9
Angry 1st derivative	7	5	6	Sunday	13	7	4	24-hour sine	11	6	4
Angry 2nd derivative	9	3	4	Survey 1	0	0	0	24-hour cosine	7	5	4
Down 1st derivative	6	6	6	Survey 2	6	1	3	Weekly cosine	10	9	11
Down 2nd derivative	4	2	2	Survey 3	7	4	5	Weekly sine	8	9	11
Did participant drink anything since the last survey (yes/no)	22	9	9								

1 = Drank/Did Not Drink person-specific model, 2 = Craving person-specific model, 3 = Want to Drink person-specific model.

Discussion

The present study sought to investigate sets of person-specific and pooled emotion and emotion dynamics variables as predictors of alcohol consumption, alcohol craving, and wanting to drink in a sample of college students. We also aimed to assess the feasibility of prediction models composed of emotion and temporal variables to accurately predict future alcohol consumption, craving, and wanting to drink. At the idiographic level of analysis, our model-building procedures returned different emotions, emotion dynamic variables, and temporal variables for each model for each participant supporting our heterogeneity hypothesis. We observed a moderately strong sample-wide prediction accuracy for future drinking behavior as indicated by a mean AUC = 0.69; corresponding to a Cohen's $d = 0.70$, a large effect size [53]. Based on each participant's unique subset of variables selected from our feature space (see Table 2), we demonstrated that accurate out-of-sample predictions of future drinking behavior two hours into the future could be made 69% of the time on average in the present models.

To compare idiographic and pooled approaches, we conducted a pooled analysis based on aggregated person-mean-centered data. This approach produced a single set of coefficients,

which were used to make predictions for participants on a person-by-person basis in person-specific holdout samples. Despite the relative age- and gender-based homogeneity of our college student sample, the idiographic approach yielded more accurate predictions and had larger effect sizes in comparison to the pooled models for all dependent variables, with the exception of the pooled model having superior sensitivity by .01 (See Fig 2). Thus, both the pooled and idiographic models on average performed equally well in predicting the presence of alcohol consumption. However, the idiographic models had superior specificity, indicating that on average, these models were better at predicting when drinking would not occur. Overall, these results indicate that the emotion dynamics within each participant were stronger predictors of future drinking events for that person than were the aggregated emotion dynamics distilled from shared variance across participants. We also found that for each model, emotions and their dynamics most associated with the specified outcome varied per person. Comprehensively, these results support our original hypotheses.

Fig 2. Density Plots of Idiographic vs. Pooled Model Results.

Observing pooled trends (see Tables 5 and 6) within the drank/did not drink model, the variables *enthusiastic*, the acceleration of *enthusiastic* (2nd order derivative), and the velocity (1st order derivative) of *stressed* and *angry* were the most predictive of whether or not participants drank. The 2nd order derivative of *enthusiastic*, where there was variability in the *changes* to their rating of enthusiasm, was associated with a specific pattern of drinking at the next time point. The variability in emotion dynamics and mixture of negative and positive emotions found in the pooled drank/did not drink models were also shown in the pooled wanting to drink models. The emotion *down*, the velocity of *down* and *angry*, and the acceleration of *calm* were most strongly associated with whether participants wanted to drink. These results of

mixed valence of emotion, and the changes of these differentially valenced emotions associated with whether someone consumed alcohol or wanted to drink alcohol replicate previous findings like those of Gottfredson & Hussong [27] and Simons et al. [29]. That is, it could be that, on average, the *variability* of emotions and not the valence of the emotions themselves leads to regulating that variability via alcohol consumption [27,29]. Given that we did not assess intent, we cannot know if participants were actively trying to regulate that emotional variability or not.

Stressed, as a dynamic process by either velocity or acceleration, or as a function of degree (0th derivative) experienced at the time of the survey, was found to be predictive of alcohol consumption for a majority of participants (N = 15). The emotions *down* and *stressed* were most predictive on average with the craving alcohol models. Research indicates that across different groups, cues associated with alcohol consumption cause subjective craving [54]. College students experience stress from a variety of sources [19]. Our results suggest alcohol use could be a way that students are coping with these and other stressors, and that feeling stressed could become a cue for craving alcohol. On average, the velocity of *stressed* was most predictive of alcohol consumption, but craving alcohol was usually triggered by the degree of feeling *stressed*.

This study demonstrated the possibility that certain and separate emotions could predict craving alcohol, and unlike drank/did not drink or wanting to drink outcomes, craving on average was predominated by negatively valenced emotions. As shown in other analyses of these data, the present analysis showed that certain days of the week, Thursday through Sunday, were common predictors of craving, and were even more common predictors in the pooled model for whether a person drank [2]. While the pooled predictors may provide some insight into which theories of alcohol use best apply to college students in general, our results indicate that the

relationship between emotions and alcohol use vary per person. How these differences impact the amount an individual drinks, how harmful their drinking behavior is, whether they influence who is more likely to develop an alcohol use disorder, or if these drinking-based outcomes significantly related to emotional regulation, remains unclear.

We would, however, like to emphasize from these findings that emotions and their dynamics are only one component in a constellation of factors that determine if and when someone consumes alcohol. Increased predictive accuracy would likely be achieved by including environmental, interrelational, and other contextual, external variables. This is reflected in our findings by the variation in how accurate the idiographic models were in prediction. For five participants (P005, P010, P015, P022, P032), the pooled model exceeded the AUC of the idiographic models. Thus, the sample average provided better prediction accuracy for these individuals than a personalized model. This finding is consistent with the parent study for the current data [2]. In addition, the models of craving and wanting to drink for P001, P010, craving for P006, P008, P023, wanting to drink for P018, and the models for drank/did not drink for P002 and P005 lack emotion variables altogether, and instead retained only time variables as predictors. For these individuals, these results suggest the current feature space provided by our EMA surveys may not have assessed what is most relevant to their drinking behavior, or that their drinking behavior has more to do with external variables, such as the college culture of drinking itself (time of day, certain days of the week, social events, etc).

Nevertheless, for most of the individuals in our study, the person-specific emotional antecedents to drinking behavior could be useful targets if a person wanted to alter their drinking behavior as indicated by the average personalized model prediction accuracy. Certainly, our findings complement previous research [33], providing an impetus to continue to examine the

connection between emotion variability, emotion regulation, and substance use. The present idiographic methodology joins the growing body of evidence that supports the use of EMA to understand individual differences in emotions pertaining to alcohol use, and affirms its value for potential clinical applications and further investigation in research. By identifying within-person emotion dynamic processes, we may have more precise cognizance of how drinking behavior comes to occur for that person within time. Despite a relatively homogenous sample, the emotional processes serving as predictors for drinking behavior varied per person.

Limitations

The present study had several limitations that deserve consideration. Foremost among these was the small, relatively homogenous sample of university students. It may be that the sample characteristics affected the predictive performance of the pooled prediction models. Future studies of alcohol consumption among college students should seek to utilize larger and more diverse samples (with particular focus on geographic-, racial/ethnic-, gender-, and college-setting diversity) to test the replicability of these model findings. While it is the emphasis of idiographic research that each participant's model will be unique and *not* necessarily generalize to others, idiographic methods should themselves generalize to future observations for the same person [2]. Thus, future studies may seek to repeat data collection after the model building process to further assess the generalizability of model performance to new data from a specific individual.

Additionally, we imputed missing observations. While there is evidence that multiple imputation of missing data can improve model performance and is an especially appropriate way to handle missing time series data pertaining to substance use [55,56], multiple imputation introduces the potential of bias into our prediction models [57]. That is, if our sample suffered

from systematic missingness, multiple imputation would likely result in biased estimates [57]. Given the nature of EMA data collection, it is impossible to know for certain if the data is completely missing at random or if the data is missing due to the outcome itself (drinking). This is common in most instances of missing data across research studies, and we chose multiple imputation to prevent errors that often occur with other methods of handling missing data [56].

The out of sample testing we conducted strongly suggests that these models will generalize well to new data. However, this relies on the untested assumption that the mechanisms driving alcohol consumption are stable over time. It is likely that substance use motives follow a developmental trajectory, where what drives someone to drink at a younger age may be very different than what drives them to drink at an older age. In an even shorter time frame, contextual factors such as increased stress due to cultural influence (such as final exams), could meaningfully alter drinking behavior in college students. To what extent these models will continue to perform the same over increasingly long periods of time is an important question that was not addressed in the present study.

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